COSE474-2024F: Deep Learning HW2

0.1 Installation

```
!pip install d2l==1.0.3
```

```
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Requirement already satisfied: exceptiongroup in /usr/local/lib/python3.10/dist-packages (from anyio<4,>=3.1.0->jupyter-server<3,>=1.8->
```

7.1 Form Fully Connected Layers to Convolutions

7.2 Convolutions for Images

```
import torch
from torch import nn
from d2l import torch as d2l
```

7.2.1 The Cross-Correlation Operation

$$\begin{aligned}0\times 0+1\times 1+3\times 2+4\times 3=19,\\ 1\times 0+2\times 1+4\times 2+5\times 3=25,\\ 3\times 0+4\times 1+6\times 2+7\times 3=37,\\ 4\times 0+5\times 1+7\times 2+8\times 3=43.\end{aligned}$$

$$(n_\textrm{h}-k_\textrm{h}+1) \times (n_\textrm{w}-k_\textrm{w}+1).$$

```
def corr2d(X, K):  #@save
    """Compute 2D cross-correlation."""
    h, w = K.shape
    Y = torch.zeros((X.shape[0] - h + 1, X.shape[1] - w + 1))
    for i in range(Y.shape[0]):
        for j in range(Y.shape[1]):
            Y[i, j] = (X[i:i + h, j:j + w] * K).sum()
    return Y
```

"@save" 주석은 허용되지 않습니다. 허용되는 값은 다음과 같습니다. [@param, @title, @markdown]

```
X = torch.tensor([[0.0, 1.0, 2.0], [3.0, 4.0, 5.0], [6.0, 7.0, 8.0]])
K = torch.tensor([[0.0, 1.0], [2.0, 3.0]])
corr2d(X, K)
```

```
tensor([[19., 25.],
        [37., 43.]])
```

7.2.2 Convolutional Layers

```
class Conv2D(nn.Module):
    def __init__(self, kernel_size):
        super().__init__()
        self.weight = nn.Parameter(torch.rand(kernel_size))
        self.bias = nn.Parameter(torch.zeros(1))

    def forward(self, x):
        return corr2d(x, self.weight) + self.bias
```

7.2.3 Object Edge Detection in Images

```
X = torch.ones((6, 8))
X[:, 2:6] = 0
X
```

```
tensor([[1., 1., 0., 0., 0., 0., 1., 1.],
        [1., 1., 0., 0., 0., 0., 1., 1.],
        [1., 1., 0., 0., 0., 0., 1., 1.],
        [1., 1., 0., 0., 0., 0., 1., 1.],
        [1., 1., 0., 0., 0., 0., 1., 1.],
        [1., 1., 0., 0., 0., 0., 1., 1.]])
```

$$-\partial_i f(i,j) = \lim_{\epsilon \rightarrow 0} \frac{f(i,j) - f(i+\epsilon,j)}{\epsilon}$$

```
K = torch.tensor([[1.0, -1.0]])
```

```
Y = corr2d(X, K)
Y
```

```
tensor([[ 0.,  1.,  0.,  0.,  0., -1.,  0.],
        [ 0.,  1.,  0.,  0.,  0., -1.,  0.],
        [ 0.,  1.,  0.,  0.,  0., -1.,  0.],
        [ 0.,  1.,  0.,  0.,  0., -1.,  0.],
        [ 0.,  1.,  0.,  0.,  0., -1.,  0.],
        [ 0.,  1.,  0.,  0.,  0., -1.,  0.]])
```

```
corr2d(X.t(), K)
```

```
tensor([[0., 0., 0., 0., 0.],
        [0., 0., 0., 0., 0.],
        [0., 0., 0., 0., 0.],
        [0., 0., 0., 0., 0.],
        [0., 0., 0., 0., 0.],
        [0., 0., 0., 0., 0.],
        [0., 0., 0., 0., 0.],
        [0., 0., 0., 0., 0.]])
```

7.2.4 Learning a Kernel

```
# Construct a two-dimensional convolutional layer with 1 output channel and a
# kernel of shape (1, 2). For the sake of simplicity, we ignore the bias here
conv2d = nn.LazyConv2d(1, kernel_size=(1, 2), bias=False)

# The two-dimensional convolutional layer uses four-dimensional input and
# output in the format of (example, channel, height, width), where the batch
# size (number of examples in the batch) and the number of channels are both 1
X = X.reshape((1, 1, 6, 8))
Y = Y.reshape((1, 1, 6, 7))
lr = 3e-2  # Learning rate

for i in range(10):
    Y_hat = conv2d(X)
    l = (Y_hat - Y) ** 2
    conv2d.zero_grad()
    l.sum().backward()
    # Update the kernel
    conv2d.weight.data[:] -= lr * conv2d.weight.grad
    if (i + 1) % 2 == 0:
        print(f'epoch {i + 1}, loss {l.sum():.3f}')
```

```
epoch 2, loss 12.753
epoch 4, loss 2.227
epoch 6, loss 0.409
epoch 8, loss 0.083
epoch 10, loss 0.020
```

```
conv2d.weight.data.reshape((1, 2))
```

```
tensor([[ 0.9921, -0.9713]])
```

7.3 Padding and Stride

```
import torch
from torch import nn
from d2l import torch as d2l
```

7.3.1 Padding

```
# We define a helper function to calculate convolutions. It initializes the
# convolutional layer weights and performs corresponding dimensionality
# elevations and reductions on the input and output
```

```
def comp_conv2d(conv2d, X):
    # (1, 1) indicates that batch size and the number of channels are both 1
    X = X.reshape((1, 1) + X.shape)
    Y = conv2d(X)
    # Strip the first two dimensions: examples and channels
    return Y.reshape(Y.shape[2:])

# 1 row and column is padded on either side, so a total of 2 rows or columns
# are added
conv2d = nn.LazyConv2d(1, kernel_size=3, padding=1)
X = torch.rand(size=(8, 8))
comp_conv2d(conv2d, X).shape
```

```
torch.Size([8, 8])
```

```
# We use a convolution kernel with height 5 and width 3. The padding on either
# side of the height and width are 2 and 1, respectively
conv2d = nn.LazyConv2d(1, kernel_size=(5, 3), padding=(2, 1))
comp_conv2d(conv2d, X).shape
```

```
torch.Size([8, 8])
```

7.3.2 Stride

```
conv2d = nn.LazyConv2d(1, kernel_size=3, padding=1, stride=2)
comp_conv2d(conv2d, X).shape
```

```
torch.Size([4, 4])
```

```
conv2d = nn.LazyConv2d(1, kernel_size=(3, 5), padding=(0, 1), stride=(3, 4))
comp_conv2d(conv2d, X).shape
```

```
torch.Size([2, 2])
```

7.4 Multiple Input and Mutiple Output Channels

```
import torch
from d2l import torch as d2l
```

7.4.1 Multiple Input Channels

```
def corr2d_multi_in(X, K):
    # Iterate through the 0th dimension (channel) of K first, then add them up
    return sum(d2l.corr2d(x, k) for x, k in zip(X, K))
```

```
X = torch.tensor([[[0.0, 1.0, 2.0], [3.0, 4.0, 5.0], [6.0, 7.0, 8.0]],
               [[1.0, 2.0, 3.0], [4.0, 5.0, 6.0], [7.0, 8.0, 9.0]]])
K = torch.tensor([[[0.0, 1.0], [2.0, 3.0]], [[1.0, 2.0], [3.0, 4.0]]])

corr2d_multi_in(X, K)
```

```
tensor([[ 56.,  72.],
        [104., 120.]])
```

7.4.2 Multiple Output Channels

```
def corr2d_multi_in_out(X, K):
    # Iterate through the 0th dimension of K, and each time, perform
    # cross-correlation operations with input X. All of the results are
    # stacked together
    return torch.stack([corr2d_multi_in(X, k) for k in K], 0)
```

```
K = torch.stack((K, K + 1, K + 2), 0)
K.shape
```

```
torch.Size([3, 2, 2, 2])
```

```
corr2d_multi_in_out(X, K)
```

```
tensor([[[ 56.,  72.],
         [104., 120.]],

        [[ 76., 100.],
         [148., 172.]],

        [[ 96., 128.],
         [192., 224.]]])
```

7.4.3 1×1 Convolutional Layer

```
def corr2d_multi_in_out_1x1(X, K):
    c_i, h, w = X.shape
    c_o = K.shape[0]
    X = X.reshape((c_i, h * w))
    K = K.reshape((c_o, c_i))
    # Matrix multiplication in the fully connected layer
    Y = torch.matmul(K, X)
    return Y.reshape((c_o, h, w))
```

```
X = torch.normal(0, 1, (3, 3, 3))
K = torch.normal(0, 1, (2, 3, 1, 1))
Y1 = corr2d_multi_in_out_1x1(X, K)
Y2 = corr2d_multi_in_out(X, K)
assert float(torch.abs(Y1 - Y2).sum()) < 1e-6
```

7.5 Pooling

```
import torch
from torch import nn
from d2l import torch as d2l
```

7.5.1 Maximum Pooling and Average Pooling

$$\begin{aligned}\max(0,1,3,4) &= 4,\\ \max(1,2,4,5) &= 5,\\ \max(3,4,6,7) &= 7,\\ \max(4,5,7,8) &= 8.\end{aligned}$$

```
def pool2d(X, pool_size, mode='max'):
    p_h, p_w = pool_size
    Y = torch.zeros((X.shape[0] - p_h + 1, X.shape[1] - p_w + 1))
    for i in range(Y.shape[0]):
        for j in range(Y.shape[1]):
            if mode == 'max':
                Y[i, j] = X[i: i + p_h, j: j + p_w].max()
            elif mode == 'avg':
                Y[i, j] = X[i: i + p_h, j: j + p_w].mean()
    return Y
```

```
X = torch.tensor([[0.0, 1.0, 2.0], [3.0, 4.0, 5.0], [6.0, 7.0, 8.0]])
pool2d(X, (2, 2))
```

```
tensor([[4., 5.],
        [7., 8.]])
```

```
pool2d(X, (2, 2), 'avg')
```

```
tensor([[2., 3.],
        [5., 6.]])
```

7.5.2 Padding and Stride

```
X = torch.arange(16, dtype=torch.float32).reshape((1, 1, 4, 4))
X
```

```
tensor([[[[ 0.,  1.,  2.,  3.],
          [ 4.,  5.,  6.,  7.],
          [ 8.,  9., 10., 11.],
          [12., 13., 14., 15.]]]])
```

```
pool2d = nn.MaxPool2d(3)
# Pooling has no model parameters, hence it needs no initialization
pool2d(X)
```

```
pool2d = nn.MaxPool2d(3, padding=1, stride=2)
pool2d(X)
```

```
tensor([[[[ 5.,  7.],
          [13., 15.]]]])
```

```
pool2d = nn.MaxPool2d((2, 3), stride=(2, 3), padding=(0, 1))
pool2d(X)
```

```
tensor([[[[ 5.,  7.],
          [13., 15.]]]])
```

7.5.3 Multiple Channels

```
X = torch.cat((X, X + 1), 1)
X
```

```
tensor([[[[ 0.,  1.,  2.,  3.],
          [ 4.,  5.,  6.,  7.],
          [ 8.,  9., 10., 11.],
          [12., 13., 14., 15.]],

         [[ 1.,  2.,  3.,  4.],
          [ 5.,  6.,  7.,  8.],
          [ 9., 10., 11., 12.],
          [13., 14., 15., 16.]]]])
```

```
pool2d = nn.MaxPool2d(3, padding=1, stride=2)
pool2d(X)
```

```
tensor([[[[ 5.,  7.],
          [13., 15.]],

         [[ 6.,  8.],
          [14., 16.]]]])
```

7.6 Convolutional Neural Networks(LeNet)

```
import torch
from torch import nn
from d2l import torch as d2l
```

7.6.1 LetNet

```
def init_cnn(module):  #@save
    """Initialize weights for CNNs."""
    if type(module) == nn.Linear or type(module) == nn.Conv2d:
        nn.init.xavier_uniform_(module.weight)

class LeNet(d2l.Classifier):  #@save
    """The LeNet-5 model."""
    def __init__(self, lr=0.1, num_classes=10):
        super().__init__()
        self.save_hyperparameters()
        self.net = nn.Sequential(
            nn.LazyConv2d(6, kernel_size=5, padding=2), nn.Sigmoid(),
            nn.AvgPool2d(kernel_size=2, stride=2),
            nn.LazyConv2d(16, kernel_size=5), nn.Sigmoid(),
            nn.AvgPool2d(kernel_size=2, stride=2),
            nn.Flatten(),
            nn.LazyLinear(120), nn.Sigmoid(),
            nn.LazyLinear(84), nn.Sigmoid(),
            nn.LazyLinear(num_classes))
```

"@save" 주석은 허용되지 않습니다. 허용되는 값은 다음과 같습니다. [@param, @title, @markdown]

"@save" 주석은 허용되지 않습니다. 허용되는 값은 다음과 같습니다. [@param, @title, @markdown]

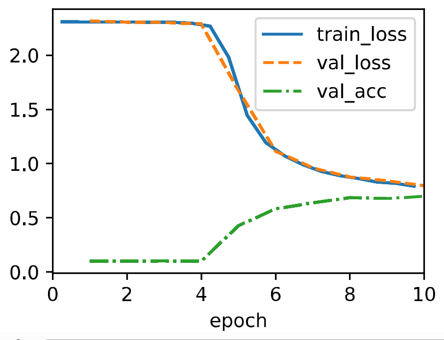
```
@d2l.add_to_class(d2l.Classifier)  #@save
def layer_summary(self, X_shape):
    X = torch.randn(*X_shape)
    for layer in self.net:
        X = layer(X)
        print(layer.__class__.__name__, 'output shape:\t', X.shape)

model = LeNet()
model.layer_summary((1, 1, 28, 28))
```

"@save" 주석은 허용되지 않습니다. 허용되는 값은 다음과 같습니다. [@param, @title, @markdown]

```
Conv2d output shape:     torch.Size([1, 6, 28, 28])
Sigmoid output shape:    torch.Size([1, 6, 28, 28])
AvgPool2d output shape:  torch.Size([1, 6, 14, 14])
Conv2d output shape:     torch.Size([1, 16, 10, 10])
Sigmoid output shape:    torch.Size([1, 16, 10, 10])
AvgPool2d output shape:  torch.Size([1, 16, 5, 5])
Flatten output shape:    torch.Size([1, 400])
Linear output shape:     torch.Size([1, 120])
Sigmoid output shape:    torch.Size([1, 120])
Linear output shape:     torch.Size([1, 84])
Sigmoid output shape:    torch.Size([1, 84])
Linear output shape:     torch.Size([1, 10])
```

7.6.2 Training

```
trainer = d2l.Trainer(max_epochs=10, num_gpus=1)
data = d2l.FashionMNIST(batch_size=128)
model = LeNet(lr=0.1)
model.apply_init([next(iter(data.get_dataloader(True)))[0]], init_cnn)
trainer.fit(model, data)
```



8.2 Networks Using Blocks(VGG)

```
import torch
from torch import nn
from d2l import torch as d2l
```

8.2.1 VGG Blocks

```
def vgg_block(num_convs, out_channels):
    layers = []
    for _ in range(num_convs):
        layers.append(nn.LazyConv2d(out_channels, kernel_size=3, padding=1))
        layers.append(nn.ReLU())
    layers.append(nn.MaxPool2d(kernel_size=2,stride=2))
    return nn.Sequential(*layers)
```

8.2.2 VGG Network

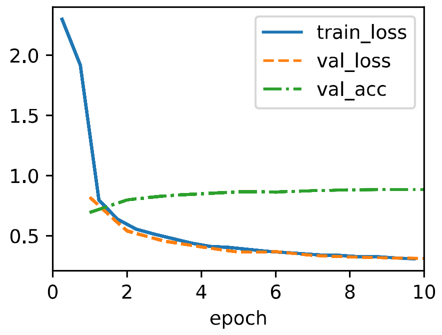
```
class VGG(d2l.Classifier):
    def __init__(self, arch, lr=0.1, num_classes=10):
        super().__init__()
        self.save_hyperparameters()
        conv_blks = []
        for (num_convs, out_channels) in arch:
            conv_blks.append(vgg_block(num_convs, out_channels))
        self.net = nn.Sequential(
            *conv_blks, nn.Flatten(),
            nn.LazyLinear(4096), nn.ReLU(), nn.Dropout(0.5),
            nn.LazyLinear(4096), nn.ReLU(), nn.Dropout(0.5),
            nn.LazyLinear(num_classes))
        self.net.apply(d2l.init_cnn)
```

```
VGG(arch=((1, 64), (1, 128), (2, 256), (2, 512), (2, 512))).layer_summary(
    (1, 1, 224, 224))
```

```
Sequential output shape:         torch.Size([1, 64, 112, 112])
Sequential output shape:         torch.Size([1, 128, 56, 56])
Sequential output shape:         torch.Size([1, 256, 28, 28])
Sequential output shape:         torch.Size([1, 512, 14, 14])
Sequential output shape:         torch.Size([1, 512, 7, 7])
Flatten output shape:    torch.Size([1, 25088])
Linear output shape:     torch.Size([1, 4096])
ReLU output shape:       torch.Size([1, 4096])
Dropout output shape:    torch.Size([1, 4096])
Linear output shape:     torch.Size([1, 4096])
ReLU output shape:       torch.Size([1, 4096])
Dropout output shape:    torch.Size([1, 4096])
Linear output shape:     torch.Size([1, 10])
```

8.2.3 Training

```
model = VGG(arch=((1, 16), (1, 32), (2, 64), (2, 128), (2, 128)), lr=0.01)
trainer = d2l.Trainer(max_epochs=10, num_gpus=1)
data = d2l.FashionMNIST(batch_size=128, resize=(224, 224))
model.apply_init([next(iter(data.get_dataloader(True)))[0]], d2l.init_cnn)
trainer.fit(model, data)
```



8.6 Residual Networks(ResNet) and ResNeXt

```
import torch
from torch import nn
from torch.nn import functional as F
from d2l import torch as d2l
```

8.6.2 Residual Blocks

```
class Residual(nn.Module):  #@save
    """The Residual block of ResNet models."""
    def __init__(self, num_channels, use_1x1conv=False, strides=1):
        super().__init__()
        self.conv1 = nn.LazyConv2d(num_channels, kernel_size=3, padding
                                   stride=strides)
        self.conv2 = nn.LazyConv2d(num_channels, kernel_size=3, padding
        if use_1x1conv:
            self.conv3 = nn.LazyConv2d(num_channels, kernel_size=1,
                                       stride=strides)
        else:
            self.conv3 = None
        self.bn1 = nn.LazyBatchNorm2d()
        self.bn2 = nn.LazyBatchNorm2d()

    def forward(self, X):
        Y = F.relu(self.bn1(self.conv1(X)))
        Y = self.bn2(self.conv2(Y))
        if self.conv3:
            X = self.conv3(X)
        Y += X
        return F.relu(Y)
```

"@save" 주석은 허용되지 않습니다. 허용되는 값은 다음과 같습니다. [@param, @title, @markdown]

```
blk = Residual(3)
X = torch.randn(4, 3, 6, 6)
blk(X).shape
```

```
torch.Size([4, 3, 6, 6])
```

```
blk = Residual(6, use_1x1conv=True, strides=2)
blk(X).shape
```

```
torch.Size([4, 6, 3, 3])
```

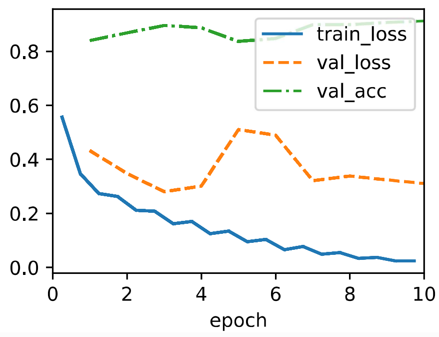
8.6.3 ResNet Model

```
class ResNet(d2l.Classifier):
    def b1(self):
        return nn.Sequential(
            nn.LazyConv2d(64, kernel_size=7, stride=2, padding=3),
            nn.LazyBatchNorm2d(), nn.ReLU(),
            nn.MaxPool2d(kernel_size=3, stride=2, padding=1))


@d2l.add_to_class(ResNet)
def block(self, num_residuals, num_channels, first_block=False):
    blk = []
    for i in range(num_residuals):
        if i == 0 and not first_block:
            blk.append(Residual(num_channels, use_1x1conv=True, strides=2))
        else:
            blk.append(Residual(num_channels))
    return nn.Sequential(*blk)


@d2l.add_to_class(ResNet)
def __init__(self, arch, lr=0.1, num_classes=10):
    super(ResNet, self).__init__()
    self.save_hyperparameters()
    self.net = nn.Sequential(self.b1())
    for i, b in enumerate(arch):
        self.net.add_module(f'b{i+2}', self.block(*b, first_block=(i==0)))
    self.net.add_module('last', nn.Sequential(
        nn.AdaptiveAvgPool2d((1, 1)), nn.Flatten(),
        nn.LazyLinear(num_classes)))
    self.net.apply(d2l.init_cnn)


class ResNet18(ResNet):
    def __init__(self, lr=0.1, num_classes=10):
        super().__init__(((2, 64), (2, 128), (2, 256), (2, 512)),
                       lr, num_classes)

ResNet18().layer_summary((1, 1, 96, 96))
```

```
Sequential output shape:        torch.Size([1, 64, 24, 24])
Sequential output shape:        torch.Size([1, 64, 24, 24])
Sequential output shape:        torch.Size([1, 128, 12, 12])
Sequential output shape:        torch.Size([1, 256, 6, 6])
Sequential output shape:        torch.Size([1, 512, 3, 3])
Sequential output shape:        torch.Size([1, 10])
```

8.6.4 Training

```
model = ResNet18(lr=0.01)
trainer = d2l.Trainer(max_epochs=10, num_gpus=1)
data = d2l.FashionMNIST(batch_size=128, resize=(96, 96))
model.apply_init([next(iter(data.get_dataloader(True)))[0]], d2l.init_cnn)
trainer.fit(model, data)
```



Discussions & Exercises

7.1 Form Fully Connected Layers to Convolutions

7.1.1 Memo

- **Key Concept:** When detecting an object in an image, the system should recognize the object regardless of its precise location, following the principle of translation invariance. For example, a pig should be recognized whether it appears at the top or bottom of an image.
- **Translation Invariance:** The network should respond similarly to a pattern regardless of where it appears in the image. This allows the system to detect objects no matter their position.
- **Locality Principle:** The network's early layers should focus on local regions of the image, with later layers capturing more global information.

7.1.2 Memo

- **MLP for Image Processing:** In a fully connected network, handling 2D images as inputs results in a large number of parameters, making it impractical for high-resolution images. Each pixel interacts with every other pixel, leading to computational challenges.

$$\begin{aligned}[\mathbf{H}]_{i,j} &= [\mathbf{U}]_{i,j} + \sum_k \sum_l [\mathsf{W}]_{i,j,k,l} [\mathbf{X}]_{k,l} \\ &= [\mathbf{U}]_{i,j} + \sum_a \sum_b [\mathsf{V}]_{i,j,a,b} [\mathbf{X}]_{i+a,j+b}.\end{aligned}$$

Translation Invariance

- **Simplification:** By assuming translation invariance, the number of parameters decreases. Instead of every weight being unique for every pixel, the same set of weights is used across the entire image. This forms the basis of a convolution, where weights are shared across spatial locations.

$$[\mathbf{H}]_{i,j} = u + \sum_a \sum_b [\mathbf{V}]_{a,b} [\mathbf{X}]_{i+a,j+b}.$$

Locality

- **Further Simplification:** By considering only local regions (nearby pixels) rather than the entire image, the number of parameters reduces even more. This results in convolutional layers, which process local patches of the image.

$$[\mathbf{H}]_{i,j} = u + \sum_{a=-\Delta}^{\Delta} \sum_{b=-\Delta}^{\Delta} [\mathbf{V}]_{a,b} [\mathbf{X}]_{i+a,j+b}.$$

7.1.3 Memo

- **Convolution in Mathematics:** The convolution operation measures the overlap between a function (e.g., image) and a filter (e.g., kernel). In deep learning, it is simplified as a sum of weighted pixel values in a local region.

$$(f * g)(i) = \sum_a f(a) g(i-a).$$

$$(f * g)(i,j) = \sum_a \sum_b f(a,b) g(i-a, j-b).$$

7.1.4 Memo

- **RGB Images:** Most images have three channels (red, green, and blue). A convolutional layer must take into account all channels, which results in higher-dimensional tensors.

- **Multiple Feature Maps:** In convolutional layers, each pixel may have multiple feature representations (e.g., edges, textures). This leads to feature maps, where each channel detects a different characteristic of the image.

$$[\mathsf{H}]_{i,j,d} = \sum_{a=-\Delta}^{\Delta} \sum_{b=-\Delta}^{\Delta} \sum_{c} [\mathsf{V}]_{a,b,c,d} [\mathsf{X}]_{i+a,j+b,c},$$

7.1 (Discussions)

1. **Translation Invariance and Locality**

- How do these principles influence the design of CNN architectures?
- Are there applications in computer vision where these principles significantly improve performance?

2. **Reduction of Parameters**

- What are the implications of reducing the number of parameters in a model?
- How does this relate to overfitting?

3. **Adding Channels**

- What are the challenges associated with processing hyperspectral images?

7.1 (Exercises)

Problem 6

To prove that convolution is symmetric, we need to show that for two functions (f) and (g), the following holds:

$$(f * g)(t) = (g * f)(t)$$

where the convolution of two functions (f) and (g) is defined as:

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau)g(t-\tau)\, d\tau$$

Proof

1. **Start with the definition of convolution:**

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau)g(t-\tau)\, d\tau$$

2. **Make a change of variable:**
Let $u = t - \tau$. Then $\tau = t - u$ and $d\tau = -du$. When τ changes from $-\infty$ to ∞, u also changes from ∞ to $-\infty$.

Rewriting the integral, we have:

$$(f * g)(t) = \int_{\infty}^{-\infty} f(t-u)g(u)(-du) = \int_{-\infty}^{\infty} f(t-u)g(u)\, du$$

3. **Recognize the form of convolution:**
The integral we obtained can be recognized as the convolution of g with f:

$$(f * g)(t) = \int_{-\infty}^{\infty} g(u)f(t-u)\, du = (g * f)(t)$$

4. **Conclusion:**
Therefore, we have shown that:

$$(f * g)(t) = (g * f)(t)$$

This demonstrates that convolution is symmetric.

7.2 Convolutions for Images

7.2.5 Memo

In this section, the distinction between **cross-correlation** and **convolution** operations is revisited in the context of two-dimensional convolutional layers in deep learning. Although convolution layers in neural networks usually perform cross-correlation, which is slightly different from strict mathematical convolution, the outputs remain unaffected.

To perform strict convolution, the kernel must be flipped both horizontally and vertically before being applied, but since kernels are learned from data, this flipping does not impact the result. Thus, convolutional layers can be viewed as performing either operation, and the terms are often used interchangeably in deep learning.

Key points:

- Cross-correlation and convolution differ in flipping the kernel.
- The learned kernel in cross-correlation is equivalent to a flipped kernel in strict convolution.
- In deep learning, the output of the convolutional layer remains the same regardless of which operation is performed.

7.2.6 Memo

This section explains the concepts of **feature maps** and **receptive fields** in CNNs. The feature map is the output of the convolutional layer, representing learned spatial features like edges and patterns. Each element of a layer has a **receptive field**, which refers to the region of the input that influences that element’s value during forward propagation.

For example, in a layer with a 2×2 kernel, the receptive field of one output element includes four elements from the input. In deeper networks, the receptive field grows, enabling detection of broader spatial features. This larger receptive field is essential for deeper layers to capture more complex patterns.

Key points:

- The feature map represents spatial features learned by the convolutional layer.
- The receptive field indicates the input region that affects each element's output.
- In deeper CNNs, receptive fields expand, allowing broader feature detection.

The term receptive field is borrowed from neurophysiology, where it was studied in experiments related to the response of the visual cortex to different stimuli, showing parallels to convolutional operations in neural networks.

8.2 Networks Using Blocks(VGG)

8.2 (Discussions)

1. Trade-offs in Network Design

- How do VGG's design principles allow practitioners to balance these factors effectively?

2. Role of Deep Learning Frameworks

- Examine how modern deep learning frameworks have transformed the way networks are constructed and configured. What are the implications of this shift for researchers and practitioners in the field?

3. Comparative Analysis of Shallow vs. Deep Architectures

- Investigate the implications of the ParNet architecture and its ability to achieve competitive performance with a shallow structure. What does this suggest about the future of CNN design and the potential for alternative approaches?

8.2 (Exercises)

Problem 1

Compared with AlexNet, VGG is much slower in terms of computation, and it also needs more GPU memory.

1. Compare the number of parameters needed for AlexNet and VGG.

2. Compare the number of floating point operations used in the convolutional layers and in the fully connected layers.
3. How could you reduce the computational cost created by the fully connected layers?

Solution

1. AlexNet: 62 miiliion, VGG: 138million
2. In AlexNet convolution layers: 724 billion, fully connected layers: 6 billion. In VGG convolution layers: 15.5 billion, fully connected layers: 13 billion
3. Use Global Average Pooling, reduce number of units, and Dropout layers.

8.6 Residual Networks (ResNet) and ResNeXt

8.6.1 Memo

- This section focuses on the class of functions F F that a specific neural network architecture can represent, given its parameters and hyperparameters. The ideal function we aim to approximate is the "truth" function $f*$ f * . However, $f*$ f * often does not belong to F F, leading us to seek the best possible function f f within this class through optimization.

$$f^*_{\mathcal{F}} \stackrel{\text{def}}{=} \underset{f}{\operatorname{argmin}} L(\mathbf{X}, \mathbf{y}, f) \text{ subject to } f \in \mathcal{F}.$$

- While regularization can help control the complexity of F F and improve consistency—meaning larger datasets typically yield better results—there's no guarantee that a more powerful architecture F' F ' will outperform F F. For non-nested function classes, increasing the size of the function class doesn't necessarily bring us closer to $f*$ f * ; in fact, it might worsen the approximation.
- The text highlights the importance of nested function classes, where a larger class contains all smaller ones, ensuring that increasing the class size enhances the network's expressive power. In deep neural networks, if an additional layer can be trained to behave like the identity function I I, the new model retains the effectiveness of the original.